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Post-Cartel Behavior: assessing the effects of antitrust policy on Brazilian fuel market

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Abstract

Papers assessing the antitrust effect on cartel cases usually take the form of a quantifying approach, measuring the impact on prices with methods like before-and-after dummy regressions, difference-in-difference, or synthetic controls designs. However, these approaches have some downsides(notably, the requirement of establishing an exogenous date or breakthrough event, based on assumptions that may not be accurate). To overcome this weakness, we applied Structural Break Analysis (Bai and Perron Test) and Markov Switching Regressions to four cases in the Brazilian fuel market (Brasilia, Belo Horizonte, São Luís and Londrina) to analyze the effectiveness of competition policies. As a comparative test between MSR and Bai Perron procedures, our paper shows that the former was more sensible to transitions between regimes, without missing breaks, and exhibited precise results. From the point of view of the antitrust policy evaluation, our findings indicate a low capacity of the antitrust authorities to extinguish price-fixing practices in targeted markets.

Keywords: collusion, antitrust policy, Brazil, fuel market, structural breaks, markov switch, policy evaluation.

1 Introduction

For decades, the Brazilian economy was characterized by oligopolized and heavily regulated markets, with some legal cartels, an outcome from the industrial policies adopted before the 1990s (Frischtak, 1980; Considera, 2002). Therefore, the practice of harms against free competition seems to be, until today, widespread in several productive sectors. That's why dealing with anti-competitive conducts, especially cartel cases with price-fixing behavior, is, probably, one of the most prominent aspects of the Brazilian antitrust authority's work. Some of the recent episodes had enormous political repercussions, such as the subway cartel in São Paulo, the bid-rigging in Petrobras' auctions, or the prosecution against JBS, the largest producer of animal protein in the world.

In most cases, these investigations turn public after major police/antitrust agents dawn raids, with extensive media coverage and many preventive arrest warrants against the scheme's leaders. However, after the cameras are turned off, what happens? Antitrust litigation can go on for a decade until the final judgment. During this period, firms and individuals end up signing leniency agreements, exempting themselves from fines or receiving discounts. All this considered, what is the post-cartel behavior of sued firms and individuals? How effective is the antitrust action? In some sense, answering these questions is the purpose of this paper, in order to analyze the effectiveness of antitrust policies in Brazil.

This paper relies on Structural Break Analysis (Bai and Perron Test) and Markov Switching Regressions, methods widely used by macroeconomists to study business cycles, but which have recently been adopted by Industrial Organization researchers, although with an emphasis on screening and not on an assessment of the effectiveness of antitrust prosecution. As an auxiliary method and a type of robustness check, we also combine these two approaches with a traditional IO conduct parameter model (Bresnahan, 1989) (which helped us to identify and get some certainty about collusion and "competition" periods).

Commonly, papers studying the antitrust effect on cartel cases take the form of a quantifying approach, trying to measure the impact on prices with methods like before-and-after dummy regressions, difference-in-difference, or synthetic controls designs. Although this kind of policy assessment is still just beginning in Brazil, there are some examples such as Lucinda and Seixas (2016); Cuiabano (2019); Afonso and Féres (2017). However, despite their importance and robustness, these approaches have some downsides. Before the analysis, researchers should establish one exogenous date or breakthrough event based on assumptions that may not be accurate. After all, they might end up with treatment effects composed of different regimes (collusion, price-wars, or competition), resulting in under or overestimates, as shown in Boswijk et al. (2019).

Unlike, the methods adopted in our paper set the breakpoints endogenously and maps the cartel behavior evolution through time. Therefore, it's possible to obtain evidence about the effectiveness of different measures against cartels implemented in different prosecution phases. It isn't our goal in this paper, but identifying correctly the collusion phases allows us to estimate, with more precision, the actual damage caused by the cartel or the real price impact of antitrust policy.

These empirical techniques were applied to four cartel cases in the Brazilian fuel market (Brasília, Belo Horizonte, São Luís, and Londrina). Expenses on transportation, in which fuel prices are very relevant, represent a share of 18% of Brazilian households' budget (higher than spending on food), according to the most recent Family Budget Survey (POF-IBGE 2017-2018). Therefore, the distributive impact of price-fixing schemes is considerable. A study from CADE (Conselho Administrativo de Defesa Econômica, Brazilian antitrust authority)[1] estimated that the Brasília's fuel cartel, a scheme that managed to raise prices by just over 8%, caused, in one year, about US$ 75 million in losses to consumers. Additionally, price-fixing in the fuel market is undoubtedly responsible for the largest number of complaints and prosecutions against Brazil's noncompetitive practices. Since 2012, the first year after the reform of the antitrust law, Brazilian authority has judged 25 cases involving irregularities in fuel retail, with 15 convictions and fines amounting to US$ 100 million. Finally, free and open access data on resale prices, wholesale prices, volumes, margins, and costs of retail fuel stations, provided by ANP (Oil Market Regulatory Agency), allow great flexibility in the econometric approach well as replications and comparisons between different studies.

Apart from the vast theoretical and empirical literature that discuss the deterrent effect of antitrust policy against cartels (as summarized in Ordóñez-de Haro and Torres, 2014), this paper is linked to yet a small but promising body of works that applies endogenously dating techniques to price-fixing cases, as Boshoff and van Jaarsveld (2019); Crede (2019); Boswijk et al. (2019); Silveira et al. (2019) (the last one adopted a Markov regime change approach based in GARCH models).

As our main contribution, we look to data not only concerned in screen cartels or estimate damages but tried to establish links between breaks in pricing behavior and real measures taken by authorities against cartels. And for this purpose, the fact that we exploited the traditional IO conduct parameter model to identify collusion regimes is a relevant innovation to the practitioner's toolbox. Additionally, as far as we know, this work is the first to systematically apply simultaneously Structural Breaks tests and Markov Switching Regressions to an extended set of cartel cases, which allow comparing the strengths and weakness of these approaches. Considering that these methods were applied to a market with known instability in collusion arrangement, our work also contributes to analyzing the two techniques' sensibility.

As a comparative test between MSR and Bai and Perron procedures, our results show that despite the relative accuracy of structural breaks effectively signaled, the breakpoints test might be less useful when we suspect recurrent collusion or instability in cartel agreements. Since we must define partitions of the sample, with a minimal size that allows the econometric estimation, it will probably miss some breaks or shorter episodes. In fact, we have observed supposedly missing breaks in our set of cartel cases (in other words, the Bai and Perron Test are somehow more vulnerable to Type II error, despite no evidence for systematically Type I

[1] Motta and Resende (2019)

errors). We also found that when markets suffer from successive periods of collusion followed by price-wars or competition phases, it's hard to interpret the results from break estimation without other information sources. Unlike, Markov Switching techniques seem to be more sensitive to transitions between regimes, without missing breaks, and gave us more precise results. Although, in some cases, we had to count on conduct parameters to identify the regimes.

From the point of view of the antitrust policy evaluation, our findings seem to indicate a low capacity of the authorities to extinguish price-fixing practices in targeted markets. The collusive behavior in fuel retailing is quite resilient, with strong recidivism or residual collusion after the antitrust intervention. Except for Brasília's cartel case, the data indicates that cartel episodes end less because of the authority's action and more due to natural changes in the market. At best, we can infer that the competition policy is acting to make price-fixing schemes more unstable.

The remainder of this paper is structured as follows. Section 2 provides a theoretical background of post-cartel behavior. Next, Section 3 discusses relevant aspects of the Brazilian fuel market. Section 4 presents our econometric procedures, and Section 5 describes our data and some modeling issues. Finally, Section 6 shows our main results and findings, and Section 7 concludes with some policy implications.

2 "Post-Cartel Behavior"

Intuitively, we can speculate the effects of antitrust action on the market affected by a cartel. The most obvious and the reason for the existence of an anti-collusion policy would be the re-establishment of adequate competition levels, which leads to a price reduction and increase in quantity sold (and the respective benefits: rising economic allocative efficiency and consumers purchase power). However, the results would not necessarily be the return to marginal cost prices. They could vary according to what would be considered natural regarding the market structure: pure competition, in the case of low concentration, or a type of oligopolistic competition (à la Bertrand, Cournot, and others) in concentrated markets, with barriers to entry.

There are no guarantees that the competition authority's action will be effective and, therefore, the market may remain collusive, and prices will be at levels of the pre-intervention phase. Finally, as can be found in the empirical literature, there are indications that, in some cases, the effects are mixed. There is not necessarily a return to competition, not even the evident maintenance of collusive practice. Markets could suffer a hysteresis effect with changes in the pricing strategy, but prices will still be above the competitive level. A whole spectrum of states could explain this new market behavior. As an example, we may face a kind of post-cartel tacit collusion. Further, depending on market conditions, the sequence of events may even allow the cartel to re-establish itself (recidivism).

Although intuitive, "post-cartel" behavior have been scarcely addressed in the theoretical literature. The primary reference is still the work of Harrington (2004), who developed a post-cartel pricing model during litigation. The model considers that firms assess the likelihood of having to compensate for the damage caused by the cartel and act strategically, maintaining, during the litigation phase, prices at levels above those of competition, generating an underestimation in damage value (the estimation of cartel's damage is, in general, based on but-for prices, which take pre and post-cartel values as reference). Erutku and Hildebrand (2010) studied the fuel market in Quebec, Canadian province, and gave some empirical validity to Harrington's model. They obtained results that show a bias between competitive prices and those observed when firms act strategically to reduce the damage estimate. According to the authors, this bias diminishes over time as the litigation process comes to an end, but it increases when the authorities file criminal charges.

In addition to Harrington's approach, on the other hand, there is vast empirical literature on the effects of anti-cartel policy, but with divergent results, as referenced in Ordóñez-de Haro and Torres (2014). Ordóñez-de-Harro and Torres extensively analyzed a group of actions taken by Spanish competition authority against cartels in the food industry. They found minimal effects. Prices have dropped slightly in some markets but got higher in others; therefore, they didn't find any evidence of actual gains for consumers. However, it's interesting to note that, according to the authors, there was a change in the pricing strategy, manifested in the notable reduction of price variance. As they suggest, this new strategy was based on prices above competitive levels but stable to minimize another raid's risks.

When, after antitrust intervention in the market, prices remain above competitive levels, we can highlight two scenarios, between many others: the re-establishment/continuity of the price-fixing scheme (recidivism), or tacit coordination between firms, facilitated by years of communication and coordination before the discovery of the cartel (residual collusion). The last case is the hypothesis advanced by Crede (2019), which analyzed the pasta market in Spain, France, and Italy. The paper shows that prices in Spain and Italy, countries virtually affected by a cartel, were higher than in France during the collusion and remained higher after the cartel's dismantling. The author argues that possible changes in local industries' structure can hardly explain these differences. González and Moral (2019) suggest a similar scenario in the Spanish fuel market. The authors showed that price levels shortly increased after the competition authority imposed fines on colluding firms and that these increases largely compensated the penalties. Therefore, it indicates that consumers are likely to bear penalties costs and that this behavior would, in hypothesis, only be possible due to some residual collusion.

The hypothesis of post-cartel tacit collusion, facilitated by the firms' experience in establishing coordination during the collusive phase, has been tested in two recent experiments. Fonseca and Normann (2012) and Chowdhury and Crede (2020) showed that a history of cooperation facilitates tacit collusion by reducing uncertainty about other firms' actions that the likelihood of this scenario is strongly linked to the success of the previous collusive phases. Crede went further and considered the effects of some antitrust measures on the probability of residual collusion. He showed that changes in the composition of firms operating in the market (rematching), for example, had a substantial effect in reducing post-cartel tacit collusion.

The possibility of re-establishing/continuing the price-fixing scheme (recidivism) after the action of the antitrust authority has received significant attention in antitrust literature, in Europe and North America, mainly (as far as we know, recidivism in the Brazilian market is a problem, not addressed yet by literature). Penalties imposed by the authorities (only administrative fines in some jurisdictions or criminal charges in others, like the USA and Brazil) may not be enough to discourage collusive behavior in some markets, especially if collusion benefits are still high and some factors facilitate price-fixing agreements. Some evidence suggests that many companies are repeat offenders in the EU, so antitrust investigations are weak enforcement. About this issue, we can cite Lande and Connor (2011); Connor and Bolotova (2006); Smuda (2014). The authors concluded that both US and European penalties for cartels are not high enough to achieve deterrence. Levenstein et al. (2015), in a sample composed of cases judged in the United States and the European Union, between 1961 and 2013, identified a high frequency of cartelization in chemical, pharmaceutical, and pharmaceutical sectors construction and fuel stations. Among the factors that facilitate collusion, they mentioned: the inelasticity of demand, market concentration, barriers to entry, industry history, and culture, as well as the presence of producer associations.

On the other hand, sometimes, even the announcement of an antitrust investigation has the power to promote changes in market agents' actions. This happened in Canada, as Clark and Houde (2014) has shown. The authors found that prices fell just after the Canadian Competition Bureau's announced, during May 2006, an investigation into the retail fuel sector. Yet, as pointed out by González and Moral (2019), they didn't analyze what happened after the case was closed, a kind of evidence that could elucidate essential aspects about the dynamic of post-cartel behavior.

3 Brazilian Fuel Market

The fuel market trajectory in Brazil is a typical example of how decades of strict economic regulation can generate persistent effects on competitive practices. Until the late 1990s, oil production and commercialization were entirely managed by the Brazilian government. There was a legal monopoly of a state-owned company, Petrobras, in upstream and refining. There were controls in prices, margins of sale, and freight in distribution and resale of automotive fuels. The first attempt to open the market can be traced back to 1996, when prices were set free in distribution and retail in some regions, like South, Southeast, and Northeast. In 1997, the Petroleum Law legally broke Petrobras' monopoly in upstream and initiated a comprehensive liberalization process through this market. But the process ended only in 2002 when prices were released in all regions, and gasoline imports were allowed.

In the period that followed the liberalization, many new wholesale traders start to operate and independent stations, resellers without any contractual relationship with fuel suppliers. Currently, Brazil fuel market has 206 wholesale traders and about 41 thousand fuel stations, 40% of which are independent (Agência Nacional de Petróleo, 2016). Despite the growing number of players in the market, there is evidence that free competition still faces cultural and structural barriers. More than a third of the charges against cartels, filled by CADE in the last decade, is related, to some extent, to the fuel market, especially the gasoline retail.

The history of official price-fixing practices is a relevant incentive for collusive practices, but other market characteristics reinforce the trend towards anti-competitive behavior. In Brazil, fuel refining is, until today, a Petrobras' non-official monopoly. The state-owned company owns 17 of the 18 refineries operating in the country, across the national territory (the only exception is Manguinhos refinery, privately owned, but whose production represents less than 2% of the total). There is also an oligopoly in the distribution chain. The largest group of firms, formed by Petrobras, Ipiranga, and Raízen, accounted for about 72% of the total volume of liquid fuels distributed in Brazil in 2015.

Reselling liquid fuels is the final step in the fuel chain and consists of receiving fuel from the distributors and serving the final consumer through fuel pumps. Stations have been free to set their prices since 2002. In theory, this would be a highly competitive market: it's local, dispersed, with many firms selling a homogeneous product. In practice, however, the number of competitors varies significantly between locations, and there are focal points and homogeneous costs due to the concentration of refining and distribution and the integrated relationship between distributors and branded stations.

Regulatory barriers to entry also characterize the fuel market. A fuel station needs both environmental licenses and authorization from ANP (Brazilian National Agency of Petroleum, Natural Gas, and Biofuels) to operate. In some cities, there is even evidence that the resellers' lobby has influenced municipalities to impose regulatory difficulties on the entry for major competitors, such as stations installed at large commercial surfaces or supermarkets (a well-documented case in charges against the Brasilia cartel, for example). Additionally, competitors' prices are easy to monitor (Brazilian legislation requires easy visualization) and are notable the resellers' unions' presence (often standardizing commercial practices). So, it's very likely the prevalence of collusive conduct in this market.

Lastly, it is worth noting that, until the end of 2016, the government informally imposed a policy to Petrobras that prevented the adjustment of fuel prices based on the variation in international oil price. We can highlight two relevant consequences for competition in the gasoline market. First, this policy hampered the conditions for importing firms, worsening Petrobras' market power problem. Second, during many years, price adjustments in refining were relatively rare. Considering that the wholesale price is the essential cost for fuel stations, this stable environment may have reduced imprevisibility and informational frictions in the market, facilitating the collusive arrangement and monitoring. Changes in refining price policy may have helped to breakdown price-fixing behaviors in recent years.

4 Econometric strategy

As stated before, the most adopted approach to measure the effects of competition policy in cartel cases relies on an estimation of a before-and-after price dummy regression. The idea is to fit a reduced form regression model as follows:

$$p_t = \alpha_1 + \alpha_2 dummy_t + \beta x_t + \varepsilon_t \tag{1}$$

Where, p_t is the price level at period t, x_t is a vector of demand and cost shifters, and the dummy variable indicates the cartel period, before the antitrust intervention ($dummy_t = 1$ if the observation in time t are included in cartel phase, $dummy_t = 0$ after the action against cartel, given the assumption that the raid ended the scheme). In the policy evaluation process, our attention is on α_2. Suppose the regression model is correctly specified, and the parameter is positive and statistically significant. In that case, we can interpret it as a positive margin over the competitive price level, strong evidence about the cartel's existence, and an argument favoring the change in market behavior after the authority's enforcement. In general, these models are suitable because they don't require much data, and their results are easy to interpret.

When the information available allows, the assessment process can be more robust if the research exploits some cross-sectional data. With the difference-in-difference approach, the econometrician uses panel data from different periods and markets (some that are affected by the cartel, the treated group, and another that aren't, the control) to estimate treatment effects. This last approach has a negative aspect: researchers should select the markets exogenously in the control group and accept an assumption about the common trend between prices from control and treatment units.

More recently, as in Motta and Resende (2019), another technique has been adopted to endogenize the control group choice or weighting. The Synthetic Control Method consists of a counterfactual construction based on a weighted mean of markets that are not treated: *synthetic controls models optimally choose a set of weights which when applied to a group of corresponding units produce an optimally estimated counterfactual to the unit that received the treatment. This counterfactual, called the synthetic unit, outlines what would have happened to the aggregate treated unit had the treatment never occurred (Cunningham, 2018).*

As was discussed in the introduction, all these models have some critical downsides. First, they assume that the changes between collusive and non-collusive periods occur only as price levels shift (in other words, only in the intercept or in the outcome means). As an example, the regression's coefficients in before-and-after are not necessarily the same through different market regimes. Cost pass-through to price can be different, as shown in the collusion literature. Second, the dummy, diff-and-diff, and synthetic controls all assume that the official cartel breakdown date or the legally established collusion period are correct, which can be extremely misleading, especially when dealing with a supposed recurrent cartel, as in the fuel market.

When relying only on official information, our results for overcharges may be overestimated, as they will possibly include price wars periods in the collusive phase. Or our impact measure may be understated if we are not considering transition periods (the beginning or breakdown of a cartel scheme isn't necessarily a sharp event, as argues Harrington, 2004). Finally, we don't know if the antitrust intervention extinguished the cartel scheme. The breakdown could be only temporary, and the traditional approaches usually ignore the post-cartel dynamics. Even when the researchers look at data in different periods, they, in practice, are groping in the dark since the date choices are still outside the model.

To evaluate the antitrust policy in the Brazilian fuel market (overcoming this bias from misspecifying effective collusion periods and accessing more accurately the actual post-cartel behavior dynamics), we will combine three approaches: tests for multiple structural changes (Bai and Perron tests), Markov Switch Regressions (MRS) and a traditional IO structural model design to estimate the market conduct parameter (Structural model).

Our tests still consider the same reduced form model shown above, with demand and cost shifters, but in an extended version of the Data Generation Process (DGP), including dynamic, as an auto-regressive distributed lags form (ARDL). Specifically in Bai and Perron's approach, for the DGP may exist m potential breaks in our data series (producing $m+1$ regimes):

$$p_t = \alpha_j + \sum_{l=1}^{n} \gamma_{jl} p_{t-l} + \sum_{l=0}^{n} \beta_{jl} x_{t-l} + \varepsilon_t \tag{2}$$

Taking the regimes $j = 0, \ldots, m$, is worth noting that the intercept, coefficients for autoregressive and for demand/cost shifters variables may vary across them. If the number and dates $(T1, ..., Tm)$ of the regime breakpoints were predetermined, the model could be estimated using standard least squares approach. But, in our application, the candidate set of break dates are unknown. To deal with this kind of problem, Bai and Perron (1998) developed an algorithm for a global optimization procedure that identifies the breaks and regression coefficients minimizing the sums-of-squared residuals that follows:

$$S(\gamma, \beta|\{T\}) = \sum_{j=0}^{m} \left\{ \sum_{t=T_j}^{T_{i+1}-1} p_t - P'_{t-l}\gamma_j - X'_{t-l}\beta_j \right\}^2 \tag{3}$$

However, this minimization is possible only over predetermined sample partitions for which the minimal segment (or the minimal percentage of observation between two breaks) are bigger than h, the trimming parameter (so, the suitable h choice depends on the number of observations in the data). After we obtained the number of breaks, the test between the null hypotheses of no breaks against m is done using standard F-statistic, a framework previously developed in Chow (1960). So, estimating successive breakpoints in a specific fuel market, we should be able to check the cartel behavior through time and evaluate if there is any coincidence between regime changes and antitrust actions against the cartel.

With Markov Searching Regression (MRS) approach, we could pursue the same goal: map the cartel behavior and asses if antitrust enforcement was able to change it. But, instead of defining a minimal segment and letting the model do the work, signaling the regimes, MRS technique requires, previously, the definition of a maximum number of states in our data series. Given the possibilities of our sample, the model computational burden, and our assumption about the possible regimes (collusion and non-collusion), our previous reduced form equation was set in two regimes like:

$$p_t = \begin{cases} \alpha + \sum_{l=1}^{n} \gamma_l p_{t-l} + \sum_{l=0}^{n} \beta_l x_{t-l} + \varepsilon_t, & s_t = 1(collusion) \\ \alpha + \sum_{l=1}^{n} \gamma_l p_{t-l} + \sum_{l=0}^{n} \beta_l x_{t-l} + \varepsilon_t, & s_t = 2(non-collusion) \end{cases} \tag{4}$$

Now, there is an assumption that the pricing behavior depends on an unobserved discrete state variable S_t, and, based on that, it's possible to estimate different DGPs for each s_t. If we assume also that ε_t are normally distributed, the parameters values can be found maximizing a mixture log-likelihood function, formed by the normal density function and the one-step ahead probability of being in one regime or another:

$$l(\alpha, \beta, \gamma, \sigma, \delta) = \sum_{t=1}^{T} \log \left\{ \sum_{m=1}^{S} \frac{1}{\sigma_s} \phi \left(\frac{p_t - \mu_t(m)}{\sigma(m)} \right) \cdot P\left(s_t = m | \Im_{t-1}, \delta\right) \right\} \tag{5}$$

Where $S_t = (1, 2)$, δ represents the parameters that determines the regime probabilities, ϕ is the standard normal density function and $\Im_{t-1}$ is the set of information in previous period. Further, we should add one more assumption in order to complete the Markov model, setting that the probability P of been in S_t follows a first-order chain with transition matrix:

$$\xi = \begin{bmatrix} \xi\left(s_t = 1 | s_{t-1} = 1\right) \xi\left(s_t = 2 | s_{t-1} = 1\right) \\ \xi\left(s_t = 1 | s_{t-1} = 2\right) \xi\left(s_t = 2 | s_{t-1} = 2\right) \end{bmatrix} \tag{6}$$

ξ is the probability of switching or remain in one regime or another. Since the Markov rule implies that the one-step-ahead probabilities depend on previous observation, the log-likelihood function in equation 5 must be estimated recursively. Following Hamilton (1989) and Kim (1994), it's possible to obtain parameters estimates and, with them, calculate filtered or smoothed probabilities off been in a regime at a specific time. In our work, we adopted the results from smoothed probabilities to describe cartel behavior evolution thought time because these probabilities are established considering all the sample information (previous and further observations).

So far, our empirical strategy must have been able to highlight, with accuracy, a regime change in observed market. However, the problem of identifying which periods are supposed to be considered collusive or non-collusive is yet to be solved. We could rely on official documents to establish when the cartel was active. This type of exogenous procedure is, instead, precisely what we have tried to avoid. We shouldn't completely ignore the information from investigations, but they must always be contrasted with the model's empirical results. Another option would be to observe the evolution of prices or gross margins (data available for fuel markets). Increases in prices or margins would be a signal that we have entered into a collusive regime. Although relevant, even this piece of information may be misleading since prices and margins are influenced by demand/cost shocks (margin data are not net from labor or other costs).

That's why, in our paper, we consider a well-known structural model, with conduct parameter, (Bresnahan, 1989) a useful tool. This model has been widely adopted and scrutinized in recent decades. Criticisms about its low power for conduct identifying (underestimation of market power), as shown in Corts (1999) and Salvo (2004), were not neglected. However, we were not interested in the absolute value of the conduct parameter but in its relative variation between regimes and structural breaks. Therefore, the conduct parameter should be an auxiliary piece of information and a way to check our findings' robustness in previous methods. Suppose that Bai and Perron's test appointed a structural break or we identify a regime-switching in MRS. Applying the parameter conduct model with dummies for the two periods in our sample will point out a change from collusion to non-collusion phase if the first period's coefficient is higher than the second one and if the variation is statistically significant. Otherwise, with insignificant variation, our finding should be considered problematic. Structural model specification and some practical issues about our data, structural tests, and Markov switching regression will be discussed in the next section.

5 Data and modeling issues

Recovering the base model in reduced form, our DGP has the generic specification below:

$$p_{gt} = \alpha + \sum_{l=1} \gamma_l p_{gt-l} + \sum_{l=0} \beta_{1l} p_{wt-l} + \sum_{l=0} \beta_{2l} w_{t-l} + \sum_{l=0} \beta_{3l} p_{et-l} + \sum_{l=0} \beta_{4l} y_{t-l} + \varepsilon_t \tag{7}$$

The core of our dataset was obtained from the Brazilian fuel regulatory agency (ANP). ANP conduces, monthly, a survey at fuel station level, which collects and turns public weighted (by sales) average values for gasoline resale, wholesale and ethanol prices (p_{gt-l}, p_{wt-l} and p_{et-l}), respectively, our dependent variable, our main cost factor and a substitute good. Additionally, as cost factor we have labor (w_{t-l}). This variable was constructed using data from the register of employed and unemployed workers (from the Ministry of Economy) and represents a variation in labor costs: the sum of wages of hired minus the sum of wages of dismissed stations employees. Finally, we tested two more variables as demand shifters: the number of vehicles registered in each location and IBC-BR, the Central Bank's economic activity index (y_t). Due to the high degree of collinearity, the data on the vehicle fleet were dropped. All data have monthly observations and were available for the period from 2004 to 2019 (until July, for B. Horizonte and Brasília cases, and November for Londrina and S. Luís). Further, to model the conduct parameter, the vehicle fleet variable was recovered, and we added gasoline sales (ANP), which covers only the period 2004-2018 (except for Brasília, where we have data from 2012 to 2019).

The literature regarding the structural break tests indicates that the results' accuracy depends mainly on the correct DGP specification (Crede, 2019). Therefore, it's recommended that the model goodness-of-fit and the structure of lags had been previously evaluated in a base period, gathering observations from a competition phase. However, in our case, this means a severe

Table 1: Variables and data sources

Variable	Source	Details
Gasoline Retail Price p_{gt}	ANP	Weighted (by sales) monthly average prices (BR Real/L)
Gasoline Wholesale Price p_{wt}	ANP	Weighted (by sales) monthly average prices (BR Real/L)
Gasoline sales q_t	ANP	Monthly sales of gasoline by wholesalers (m^3)
Ethanol p_{et}	ANP	Weighted (by sales) monthly average prices (BR Real/L)
Labor Costs w_t	Register of Employed and Unemployed workers, Ministry of Economy)	Sum of wages of hired minus the sum of wages of dismissed stations employees (BR Real)
Economic Activity Index y_t	Brazilian Central Bank	IBC-BR: Monthly economic activity index (base: Jan-2003)
Vehicles fleet v_t	Dentram (Brazilian Traffic Department)	Montlhy local vehicle fleet

weakness since there is no way to guarantee that we know in advance which observations can be considered at the competition regime. As a second-best option, we chose to adjust the model on a sample partition before what was officially delimited, in the antitrust proceedings, as the cartel period. However, this DGP may contain collusive periods not identified by the authorities, and, therefore, from now on, the results of the structural break test should be analyzed with caution. We should first combine all the information available in our results to state whether the regime change means a transition from non-collusive to collusive periods or otherwise (this highlights the importance of using other methods in our inference processes, such as MRS and conduct parameter).

Table 2: Specification of DGPs (data before official cartel period)

Variable	Brasília	Belo Horizonte	São Luís	Londrina
	0.009	0.006*	0.009	-0.000674
Constant	(0.008)	(0.003)	(0.005)	(0.010)
	0	0	0	0
	-0.323***	-0.392***	-0.314493***	-0.128795
Gasoline retail price(-1)	(0.103)	(0.091)	(0.086)	(0.125)
	1	1	1	1
	2.137***	1.182***	1.279***	1.115***
Gasoline wholesale price	(0.313)	(0.0888)	(0.417)	(0.398)
	0	0	0	1
	-12.821***		3.552	5.587194
Gasoline wholesale price sqr.	(4.035)		2.933	(7.013)
	0		0	0
	-0.139*	0.068**	-0.042	-0.054
Ethanol	(0.104)	(0.032)	(0.145)	(0.101)
	0	1	0	0
	0.0002	0.00003	0.007***	0.0002
Labor costs	(0.0003)	(0.0002)	(0.002)	(0.000747)
	0	0	4	1
	0.008**	0.0005	-0.007**	-0.002
Economic Activity Index (IBC-BR)	(0.004)	(0.002)	(0.003)	(0.005)
	2	0	1	0
Adjusted R^2	0.585	0.885	0.752	0.588
Observations	47	35	32	35
Period	2004M01 2007M12	2004M01 2006M12	2004M01 2006M12	2004M01 2006M12

Dependent variable: retail gasoline prices (source: ANP). All variables are in first differences and adjusted for seasonality. Coefficients with ***, **, and * are significant at level 1, 5, and 10%. The third row of each variable indicates the lag that was used in the regression.

The results from fitting a DGP for each of the four markets analyzed are displayed in table 2 and the diagnostics tests are in table 3. It's worth noting that our lag structure is as parsimonious as possible, only enough to fit the model adequately. Since Bai and Perron's algorithm has a partitioning procedure based on the trimming parameter, the inclusion of many regressors could compromise the convergence proprieties of our estimation. In general, the coefficients show an expected pattern, with some deviations, especially on demand shifters (there are negative signs in Ethanol and IBC-BR coefficients, what might be explained by Rotemberg and Saloner (1986) model of 'price wars' during business cycles booms, considering that we didn't rule out the possibility of including observations from cartel period). Another relevant aspect in our DGPs is that there is heteroskedasticity or serial correlation in São Luís and Londrina. Therefore, we must process their structural break tests with robust standard errors.

Table 3: DGPs residual diagnostic tests

Test	Null hypothesis	Brasília		Belo Horizonte		São Luís		Londrina	
		Statistic	*p-value*	Statistic	*p-value*	Statistic	*p-value*	Statistic	*p-value*
Jaque-Berra	Normally distributed	0.39	0.81	0.18	0.91	0.97	0.61	7.3	0.02
Breusch-Pagan-Godfrey	Homoskedasticity	4.32	0.63	9.67	0.28	6.5	0.36	16.5	0.02
Breusch-Godfrey	No serial correlation	3.68	0.15	2.6	0.11	5.1	0.07	2.7	0.25
Ramsey RESET	Correct specification	0.63	0.52	0.84	0.40	1.18	0.24	1.2	0.23

We must state one last observation about structural break tests. There is no predefined ideal trimming parameter. Additionally, the Bai and Peron's test can be conducted allowing, or not different error distributions through the breaks, and neither there is an ideal choice. A robust way to deal with these issues is to estimate our breaks with different trimming parameters and homogeneity and heterogeneity in error distributions to check if the results are consistent.

In the case of Markov Switching Regression, as highlighted by Boshoff and van Jaarsveld (2019), the principal practical aspect is the model sensibility to which variables can vary between regimes (in MRS, not only the coefficients may change but also the error variance). That's why the initial step of our estimation is a model selection based on information criterion.

As stated before, the variation in our sample doesn't allow more than two regimes, so the decision was only about regime-dependent variables and error variances. As we can see from table 4 (the best model is in bold), in Brasilia case, there is regime-dependence on intercept, auto-regressive term, wholesale price, ethanol, and error variance. In the Belo Horizonte fuel market, the error variance is neither regime determined nor the labor coefficient. In São Luís, ethanol, IBC-BR, and labor are not dependent. Londrina didn't observe regime variation in error variance, ethanol, and labor variables.

Table 4: Model selection by information criterion (Akaike)

Switching parameters	Brasília	B. Horizonte	São Luís	Londrina
C	-	-	-	-
CAR	-	-3.419	-2.086	-2.540
CARW	-2.252	-3.525	-2.114	-2.547
CARWE	-2.261	-3.639	-2.105	-2.540
CARWI	-2.258	-3.604	-2.105	**-2.551**
CARWEI	-	**-3.641**	-	-2.543
CARWL	-2.251	-3.515	-2.105	-2.545
CARWS	-	-3.554	**-2.377**	-
CARWSE	**-2.349**	-3.630	-2.355	-2.493
CARWSI	–	-	-2.366	-2.360
CARWSL	-	-	-2.367	-

Abbreviations: (AR) Gasoline retail(-1), (C) Constant, (W) Gasoline wholesale, (E) Ethanol, (I) IBC-BR, (L) Labor costs, (S) Error variance. All prices in the estimation were deflated using INPC (Brazilian consumer's inflation index).

Finally, for the conduct parameter, it's necessary to define a structural model formulated by a system of a demand and a pricing equations. For demand, we have a linear specification as follows:

$$q_t = \alpha + \beta_1 p_{gt} + \beta_2 p_{et} + \beta_3 y_t + \beta_4 v_t + \varepsilon_t \tag{8}$$

Where, q_t is the monthly quantity of gasoline (in m^3) sold in the market analyzed; p_{gt} and p_{et}, are, as before, gasoline retail and ethanol prices; y_t is the economic activity index; and v_t is the local vehicle fleet.

Then, there is a pricing equation (as usual, formed by marginal cost and marginal revenue equality):

$$p_{gt} = \lambda \frac{q_t}{\beta_1} + \gamma_0 + \gamma_1 p_{wt} + \gamma_2 w_t + \varepsilon_{pt} \tag{9}$$

p_{wt} and w_t are cost factors (gasoline wholesale price and labor); β_1 is a coefficient taken from the demand estimation, and λ is the conduct parameter. This parameter nests a set of possible market structures: competition, if equals 0, monopoly or perfect collusion, if equals 1; cournot-nash, if equals $1/N$, where N is the number of firms. Or it may represents an intermediate market power index if the values are different from benchmarks models. To identify the regimes/periods highlighted by our approach as collusive or non-collusive, it's necessary to add dummies interacting with conduct parameters (we found that Markov probabilities are more reliable to distinguish periods, so we use its results to set the dummies). Therefore, the pricing equation took the form below:

$$p_{gt} = \sum_{p=1}^{n} dummy_{pt} \lambda_p \frac{q_t}{\beta_1} + \gamma_0 + \gamma_1 p_{wt} + \gamma_2 w_t + \varepsilon_{pt} \tag{10}$$

The subscript p is the period, n is the number of periods signaled by the Markov approach (in our setting, this n periods can be in two regimes, collusion or non-collusion), and λ_p is the conduct parameter specific for each period. In a specific period, If this parameter is close to 0, it is plausible that we should identify it as a competition phase. Values departing from 0 may be seen as more collusive ones (remembering that this approach underestimates the true conduct, and we are not expecting values close to 1). To test if the variation between parameter/periods is significant, we applied Wald tests comparing a period with the previous one. It's worth noting that the system of equation has endogenous variables (q_t and p_{gt}). We need to proceed with our estimation with instrumental variables in a two-step least-squares approach for unbiased coefficients. In our case, the instruments were excluded cost and demand factors and lagged gasoline and ethanol prices.

6 Results

This section will provide the main results from our econometric strategy, focusing on describing the cartel behavior during antitrust enforcement (or what has been named post-cartel behavior). We will first present a brief historical context for each of the markets analyzed, highlighting some authorities' measures. Then we will confront these events with breaks estimated by Bai and Perron's test and with the smoothed probabilities of being in collusion regime provided by Markov switching method. Finally, it will be checked if the conduct parameters are sensitive to changes pointed out by our approach. Additional results from our estimations are in the paper's appendices A and B.

6.1 Brasília

Despite not been closed yet, the Brasilia's cartel case is, in many senses, extremely relevant in the recent Brazilian antitrust history. First, this cartel managed to raise prices in the wealthiest and highly educated city and the country's capital. It was operating literally at the neighborhood of Antitrust Authority's (CADE) headquarter. Moreover, the cartel scheme was, somehow, common knowledge years before the antitrust action. Maybe because of these former aspects, CADE, and other authorities, acted with great strengthen during and after the Dubai Operation (the initial raid against cartel's members), imposing preliminary penalties and conditions on firms and individuals that haven't been seen in fuel markets before.

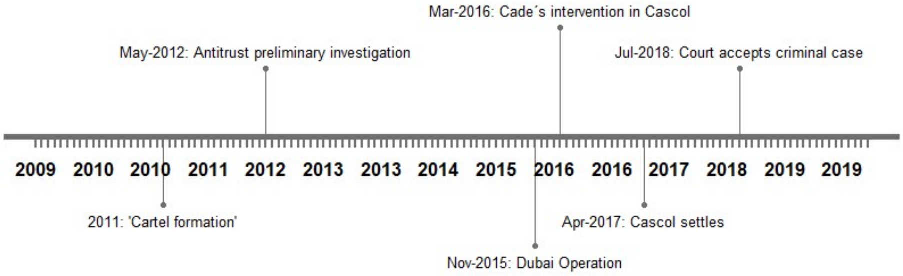

Figure 1: Brasilia - timeline

Officially, the cartel investigation began in 2009 after a complaint. In May 2012, the firms received a formal notification about the preliminary proceeding, and this, hypothetically, could be considered the first possible breakdown event. But, apparently, the cartel remained active. In November 2015, CADE and judicial authorities conducted the first phase of the Dubai Operation, which fulfilled dozens of search and seizure warrants, temporary arrests, and coercive bench.

After the operation, Cade continued to screen the market and found that the prices were still above the competitive level. Besides, the evidence gathered in the investigation demonstrated that the company Cascol, the leader in Brasilia's fuel retail market, was also one of the cartel's leaders. That's why, in March 2016, the antitrust authority imposed a preventive intervention in the Cascol administration, appointing an independent administrator to manage the fuel stations. Also, in 2016, in May, there was another raid, Dubai Operation II, which fulfilled more search and seizure warrants. In April 2017, Cade's Administrative Court approved a Termination Commitment Agreement signed with Cascol. Under this agreement, the company paid an amount of US$ 20 million in fees and made a disinvestment commitment, accepting to sell several of its fuel stations. In July 2018, the Brazilian federal Court received the criminal charges against cartel members.

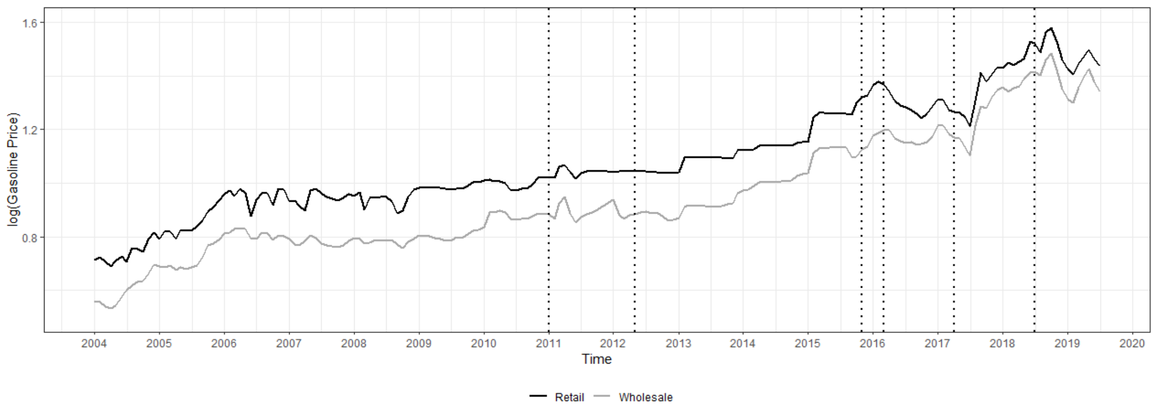

Figure 2: Brasília - gasoline price evolution (2004-2019). The dashed lines indicate cartel dates, as shown on the timeline.

When judicial authorities presented criminal charges at Court, they considered that the cartel scheme began in early 2011. If we look at the price series (figure 2) we found a small price increasing around January-April 2011, but it's temporary and follows an increase in wholesale values. In another relevant event date, May 2012 (when firms were informed about antitrust investigation), prices remained stable, although there was some gasoline costs variation. Therefore, there is no apparent behavior indicating that the cartel was somehow affected. Going further, after the first phase of Dubai Operation, what is possible to retain is that prices were rising and that antitrust action didn't reverse this trend. Unlike, the next three events, especially CADE's intervention, were followed by decreases in prices, although it's no possible yet to disentangle from wholesale price evolution. So, the price behavior is not informative; that's why we must rely on other approaches, hoping that they will give clear information.

Table 5: Brasília - structural breaks dates

h	Homogeneity								
0.10	may/10	aug/11	nov/12	-	-	may/15	may/16	-	feb/18
0.15	nov/10	-	nov/12	-	sep/14	-	mar/16	-	feb/18
h	Heterogeneity								
0.10	may/10	aug/11	nov/12	dec/13	-	may/15	may/16	may/17	mai/18
0.15	nov/10	-	nov/12	-	sep/14	-	mar/16	-	feb/18

Global vs m-breaks Bai and Perron Test (significant at level 5%)

Unfortunately, results from structural break tests are also unclear (table 5). The break dates vary greatly with trimming parameters. Even when exists a match between them; there isn't certainty about what kind of regime (collusion or non-collusion) is operating between breaks. A problem expected in our approach because the sample comes from a market where the collusion is probably unstable (given the high number of firms). Price-fixing schemes can operate for a long time, but they will be affected by recurrent price wars, and the number of breaks may highlight this. Despite unclear results, it's worth noting that there is no break in early 2011, neither around November 2015 (Dubai Operation). But there is a break around March-May 2016 when CADE appointed an independent administrator to manage Cascol stations.

In figure 3, we added another layer to the price evolution graph. The continuous black line indicates the smoothed probabilities of being in a collusion regime (resulting from the estimation of a Markov Switching Regression Model). The dashed black lines are the break dates resulted from Bai and Perron's test (with homogeneity in errors distribution and trimming parameter $h = 10$). It's worth noting that there are some coincidences between breakpoints and probabilities changes, which give credibility to our results. There is also another relevant aspect. Structural break tests lost several regime changes because they are too short (it identified only the beginning of 2010's apparently price war, and only the endpoint of another one in 2015, as an example). On the other hand, the structural break approach was sensible to behavior changes between 2011 and 2013, which did not affect the probabilities.

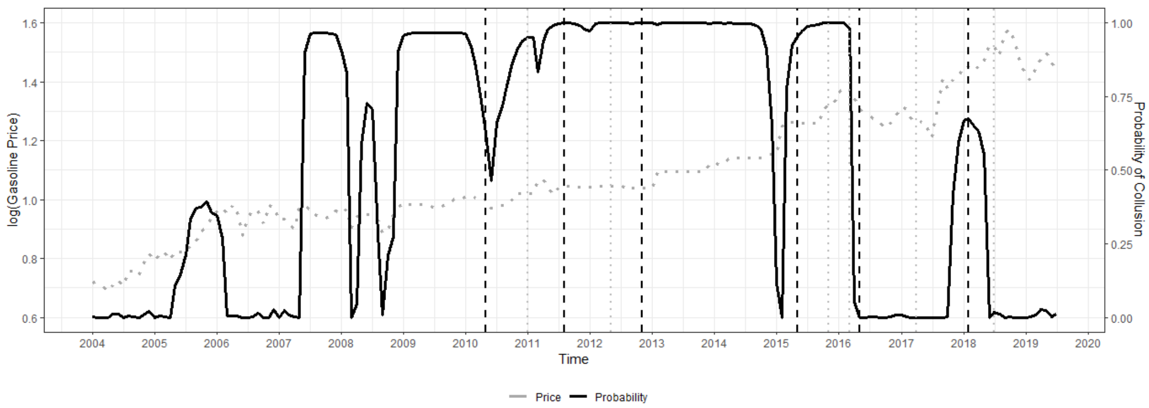

Figure 3: Brasília - collusion probabilities and breaks (2004-2019). The gray doted lines indicate the price evolution and official cartel dates, the black dashed lines are the breaks estimated in Bai Perron Test (homogeneity and $h = 10$).

On the cartel's behavior through antitrust litigation, it's possible to retain some points. First and most important: the initial raid against cartel members (Operation Dubai I) was ignored by the agents. They were supposedly re-establishing the cartel after a price war at the beginning of 2015 and remained with collusive practices after the antitrust action. But, apparently, measures taken after Dubai Operation were enough to breakdown the cartel (and the intervention in the Cascol administration seems to have been the most effective). There is a perturbation in this trend around 2018, but at that time, Brazil suffered from a truck drivers' strike and saw fuel shortages, which may have affected the outcomes from the market. Second point: Brasília's cartel probably was longer than judicial authorities seem to believe. Our results indicate that it might have begun in 2007, not in 2011, and were relatively persistent until 2016.

Table 6: Brasília - conduct parameter

Periods	Parameter	F	p-value
Jan-2012 to Feb-2016	0.089	-	-
After Mar-2016	0.019	65.73	0.000

F-statistics are testing the significance of variation on conduct parameter between periods. Data from quantity for Brasilia market are more precise (include only gasoline sold at local stations), but observations are available only from 2012.

However, how can we be sure about the fact that probabilities are pointing out a collusive regime? Our approach took the conduct parameter variation to deal with this question. Until 2016, the conduct parameter was estimated at 0.089. It's not that high, but after March 2016, it fell considerably, and this change was highly significant, as can be checked in table 6. Until July 2019, the period covered by our sample, antitrust intervention can be considered successful. As informed before, the paper authored by Motta and Resende (2019) argues in favor of our finding. They applied a Diff-and-Diff approach using the same ANP database and found a decrease in gasoline prices of about 8% after cartel breakdown in Brasília.

6.2 Belo Horizonte

Belo Horizonte's cartel had a fundamental difference compared with Brasilia's case: antitrust authority was not a protagonist at the beginning of the investigation, in 2008. Mão Invisível (Invisible Hand) Operation, the accusation inaugural, was conducted by criminal authorities with the support of Brazilian federal police. There wasn't any market intervention, despite the fulfillment of temporary prison warrants. Only in 2017, CADE imposed fines on colluding firms and individuals after they signed a Termination Commitment Agreement.

About this cartel case, we must highlight some important dates: judicial authorities considered that the cartel period spanned from March 2007 to April 2008; police's dawn raid against scheme members happened in July 2008, with almost 30 prison warrants; firms and individuals settled with CADE in April 2017, and CADE's Administrative Court judged and condemned the cartel in April 2019. Scheme members were fined in values that summed US$ 35 million.

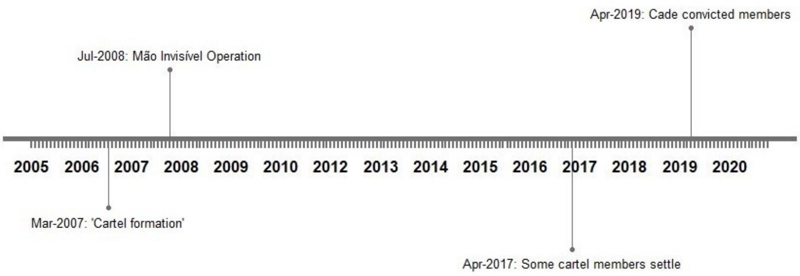

Figure 4: Belo Horizonte - timeline

Looking at price series (figure 5), we can identify a shift at the neighborhood of the official date for cartel beginning, but we are still struggling to disentangle the cartel effect from cost shocks. The police raid, surprisingly, aren't so evident in price evolution. On the other hand, when firms settled with CADE, prices showed a considerable raising pattern, although, once again, the movement is following the cost trend.

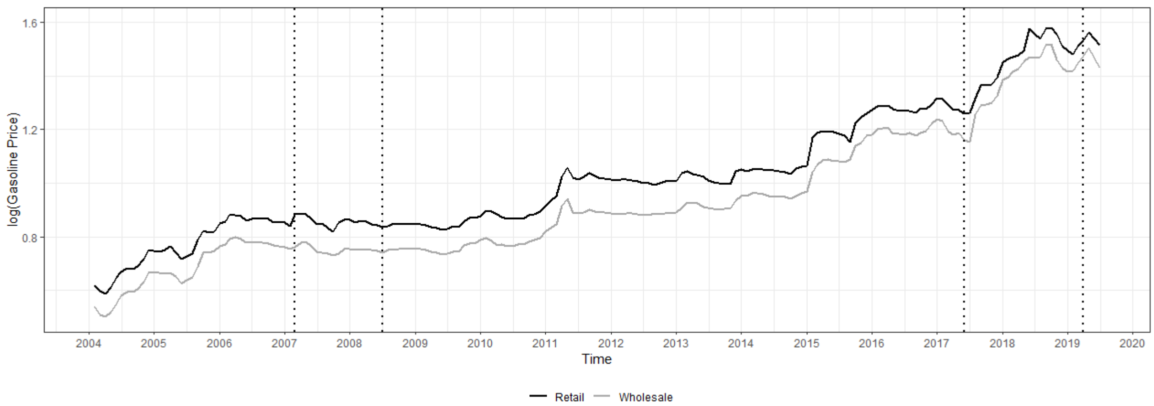

Figure 5: Belo Horizonte - gasoline price evolution (2004-2019). The dashed lines indicate the official cartel dates, as shown on the timeline.

Now, checking table 7, the structural break tests are still not so informative, with a significant divergence between the two trimming parameters. However, the relevant information here is that there is no break date that captured the dawn raid's effects or, later, the settlement or the administrative judgment. It's worth noting that November 2010, January-February 2013, and September-December 2015 seem to be signaling pattern changes in Belo Horizonte's fuel market.

Table 7: Belo Horizonte - structural breaks dates

h				Homogeneity					
0.10	apr/08	-	nov/10	-	jan/13	jun/14	sep/15	dec/16	apr/18
0.15	-	jan/09	nov/10	-	feb/13	-	dec/15	-	oct/17
h				Heterogeneity					
0.10	apr/08	-	apr/10	aug/11	jan/13	jun/14	sep/15	dec/16	apr/18
0.15	-	jan/09	nov/10	-	feb/13		dec/15	-	oct/17

Global vs m-breaks Bai and Perron Test (significant at level 5%)

As in Brasilia's case, the Markov Switching Regression method can better overview the cartel behavior through time. Let's observe the data from figure 6. Once again, we saw some matching between structural breaks and regime changes in MRS probabilities, but shorter episodes are still missing in Bai and Perron's approach.

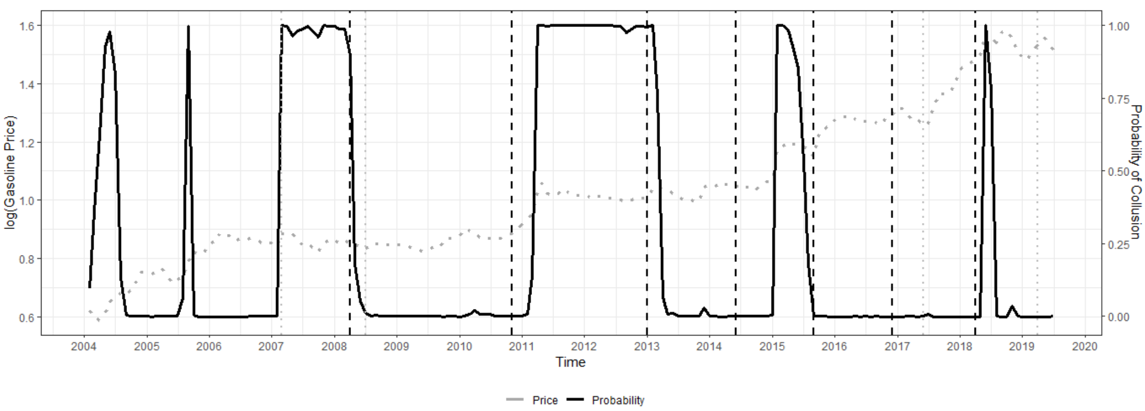

Figure 6: Belo Horizonte - collusion probabilities and breaks (2004-2019). The gray doted lines indicate the price evolution and official cartel dates, the black dashed lines are the breaks estimated in Bai Perron Test (homogeneity and $h = 10$).

What is relevant about the cartel behavior is that we can not be sure if the dawn raid broke the first cartel appearance in 2008 (it seems to be naturally fading before the police operation). In the absence of antitrust measures, the market evolution apparently offered conditions to re-establish the collusive scheme three years later, at the beginning of 2011. Supposedly, the cartel faded away at the beginning of 2013 and reappeared briefly in 2015. Our findings also indicate that it's not operating recently, but there isn't a clear relationship between its breakdown and the antitrust authority's direct actions. At best, we might state that the successive measures (like Termination Commitment Agreement and the 2019 judgment) helped prevent the cartel's resurgence.

Table 8: Belo Horizonte - conduct parameter

Periods	Parameter	F	p-value
Jan-2004 to Feb-2007	0.052	-	-
Mar-2007 to Mar-2008	0.088	17.42	0.000
Apr-2008 to Jan-2011	0.033	33.33	0.000
Feb-2011 to May-2013	0.068	46.25	0.000
After Jun-2013	0.017	135.97	0.000

F-statistics are testing the significance of variation on conduct parameter between periods.

Finally, the conduct parameters in table 8 reinforce our findings. The values were higher for periods with high probabilities of been in a collusive regime (March 2007 to March 2008 and February 2011 to May 2013) and fell considerably after 2013. All the parameter changes were significant, according to Wald's tests.

6.3 São Luís

Like Belo Horizonte's cartel, in Sao Luís' case, the investigations, initiated in 2011, were held by the criminal authorities (Cronos Operation). The antitrust litigation was opened only in 2014 after CADE received transcripts of telephone wiretaps authorized by the Court, as well as other evidence forwarded by criminal authorities. Recorded conversations showed that the owners of stations in São Luís agreed to set higher prices and induced other stations to do the same, between February and March 2011. Besides, the investigations revealed the existence of market-sharing agreements, coordinated by the fuel retailer's association.

To our analysis, it's worth retaining the following essential events/date. For criminal and antitrust litigation, the cartel period was defined between February and March of 2011, during which criminal authorities conducted Cronos Operation (with telephone wiretaps). CADE filled the antitrust case in October 2014, and the administrative judgment occurred in June 2017. Firms and individuals that participate in the cartel were fined US$ 4,2 million approximately. Finally, in September 2018, fuel retailers settled in Court and signed a commitment not to exchange information about prices.

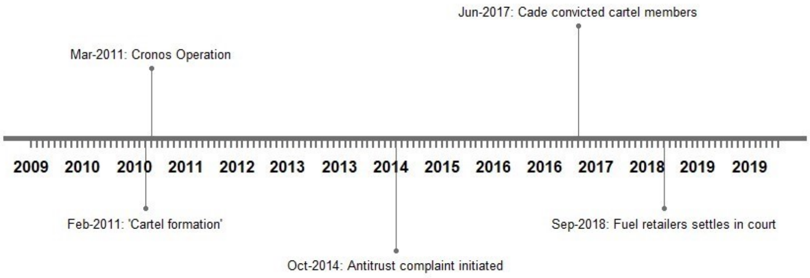

Figure 7: São Luís - timeline

If we take the price series in the São Luís fuel market (figure 8), there is a sharp increase during the beginning of 2011. The wholesale price also went up, but its pattern seems to be more moderate. However, this behavior apparently was not sustainable, maybe because the criminal authorities turned public the cartel investigation at the same period. Running through the chain of events, prices got higher after the beginning of antitrust investigation and decreased following the two last events (CADE's judgment and agreement in Court), but we don't yet have enough evidence to connect these movements with antitrust measures.

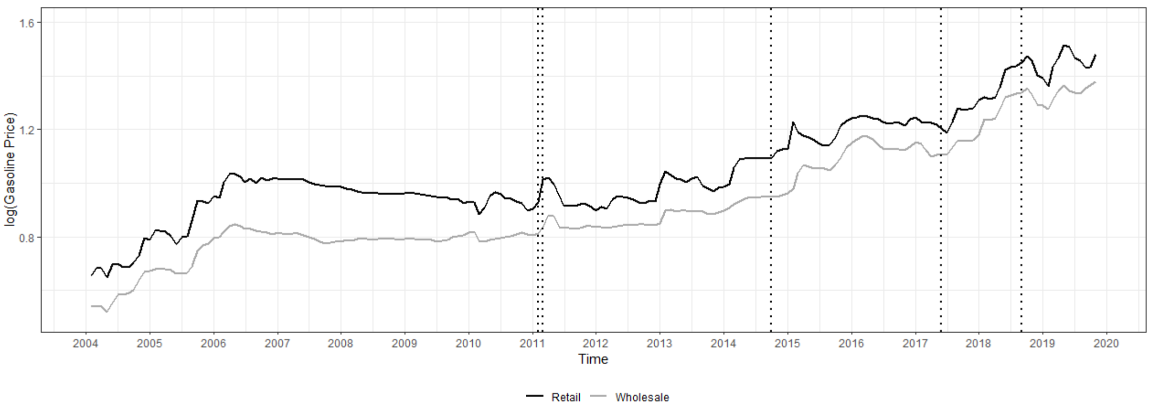

Figure 8: São Luís - gasoline price evolution (2004-2019). The dashed lines indicate the official cartel dates, as shown on the timeline.

Alone, with nothing but the break dates, our structural change approach (table 9) is still more confusing in São Luís' Cartel case. However, the number of breaks and the divergence between the two trimming parameters are strong evidence of the cartel's instability. Relevant events during antitrust litigation seem, instead, to be ignored by break dates. The only and important exception are the dates from the beginning of 2011, which indicates that probably happened some changes in the period considered by authorities as to the cartel phase.

Table 9: São Luís - structural breaks dates

h					Homogeneity					
0.10	nov/08	-	mar/10	apr/11	nov/12	dec/13	-	jan/15	feb/16	mar/17
0.15	-	may/09	-	jan/11	sep/12	-	may/14	-	jan/16	-
h					Heterogeneity					
0.10	nov/08	-	mar/10	apr/11	nov/12	dec/13	-	jan/15	feb/16	mar/17
0.15	-	may/09	-	jan/11	sep/12	-	may/14	-	jan/16	-

Global vs m-breaks Bai and Perron Test (significant at level 5%)

Cartel's probability, plotted in figure 9, depicts a volatile scenario. Antitrust and criminal authorities were partially right in defining the beginning of cartel in February or March 2011, but, in fact, the agreement between station owners probably was an attempt to re-establish the scheme that operates previously, between 2006 and 2010. This attempt wasn't totally successful, and there are successive comings and goings in price-fixing behavior. This behavior is a reasonable explanation for the results from the structural breaks method (which, by the way, are less precise, but not so divergent with MRS findings, as the other two cases analyzed).

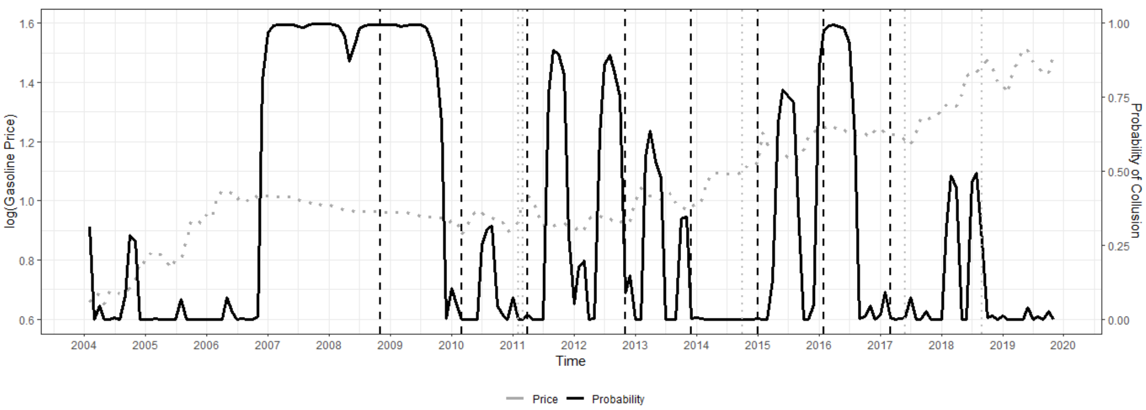

Figure 9: São Luís - collusion probabilities and breaks (2004-2019). The gray doted lines indicate the price evolution and official cartel dates, the black dashed lines are the breaks estimated in Bai Perron Test (homogeneity and $h = 10$).

We have evidence that actions against the cartel didn't extinct collusive behavior in the fuel market. It's relevant to notice that there was residual collusion with very probable cartel episodes until 2016. However, they are very short and less effective than the one registered before 2010 (authorities' work may have created conditions for this instability, but, unfortunately, our approach is not enough to disentangle its effects from market changes).

Table 10: São Luís - conduct parameter

Periods	Parameter	F	p-value
Jan-2004 to Oct-2006	-0.032	-	-
Nov-2006 to Dec-2009	0.059	63.89	0.000
After Jan-2010	-0.002	8.59	0.003

F-statistics are testing the significance of variation on conduct parameter between periods.

Once more, the conduct parameter method gave some certainty about our analysis, showing that the λ_p was higher between 2006 and 2009 (the cartel's stable period) and significantly decreased before 2010 (the phase with short collusive phases).

6.4 Londrina

Londrina's cartel was extensively analyzed by Cuiabano (2019), who found that the scheme managed to raise gasoline prices 3.6% to 6.6% above the competitive level. Her estimates adopted, as a reference, information from antitrust charges, which indicate that the collusive period spanned from April-May to August 2007. The official' end date' for the scheme coincides with Medusa III Operation, a dawn raid executed by Paraná state's police and antitrust authorities. This raid fulfilled 16 search and seizure warrants in stations located in Londrina and neighbors' municipalities. A previous police investigation, with telephone wiretaps, showed that collusion started when one of the retailers dropped its price and started a price war between stations in the Londrina region. So, in April-May 2007, fuel retailers initiated conversations to agreed on price increases and readjustments dates. Cartel's leaders used retailer's association to expand their agreement to all associates.

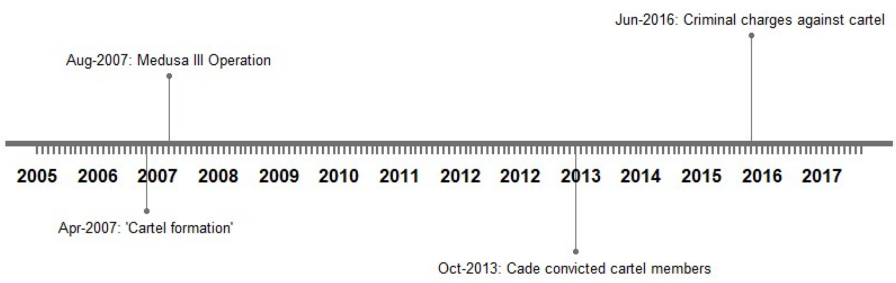

Figure 10: Londrina - timeline

In addition to the cartel period and Medusa III operation, we must retain two more relevant events. CADE administrative court convicted the collusive behavior six years later, in October 2013, with penalties summing up to more than US$ 2,5 million. Criminal authorities presented in Court charges against the cartel after nine years, in June 2016. There was one last event, in February 2020, Paraná's Court extinguished the case because they exceeded the maximum time for a criminal case, but our data set doesn't include this period.

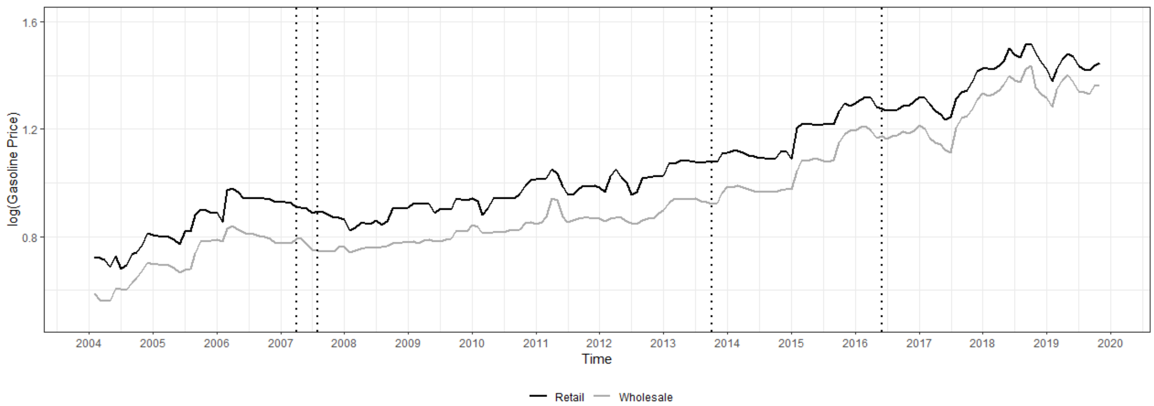

Figure 11: Londrina - gasoline price evolution (2004-2019). The dashed lines indicate the official cartel dates, as shown on the timeline.

As a naive approach, observing the price series doesn't offer anything more than some clues about the effects of antitrust action, as stated in all previous cases. The structural changes method, instead, provides more pieces of information, although noisy. There aren't structural changes in the neighborhood of August 2007 (Medusa III Operation), but there are shifts around October 2013 and June 2016.

Table 11: Londrina - structural breaks dates

h	Homogeneity								
0.10	aug/08	dec/09	may/11	aug/12	nov/13	apr/15	aug/16	–	aug/18
0.15	–	jun/09	aug/11	–	jul/13	oct/15	–	dec/17	–
h	Heterogeneity								
0.10	aug/08	dec/09	may/11	aug/12	nov/13	apr/15	aug/16	–	aug/18
0.15	–	jun/09	aug/11	–	jul/13	oct/15	–	dec/17	–

Global vs m-breaks Bai and Perron Test (significant at level 5%)

Adding another layer again to our price evolution graph to show the collusion probabilities and the structural breaks (figure 12), what we get is bad news to antitrust authorities. The cartel formation captured in criminal authorities' telephone wiretap was, actually, an attempt to avoid the cartel breakdown, caused by the price war registered at the beginning of 2007. It's worth recognizing that Medusa III Operation may have been the cause for the temporally end of the cartel between 2008 and 2009, but our results show that the collusion behavior was persistent, with some instability, until the end of 2015. Markov switching probabilities also revealed a relatively mild disturbance after the cartel's conviction at CADE's Administrative

Court. However, the collusive scheme kept operating for another two more years, and it's quite likely that the recent period of competition is due to market conditions.

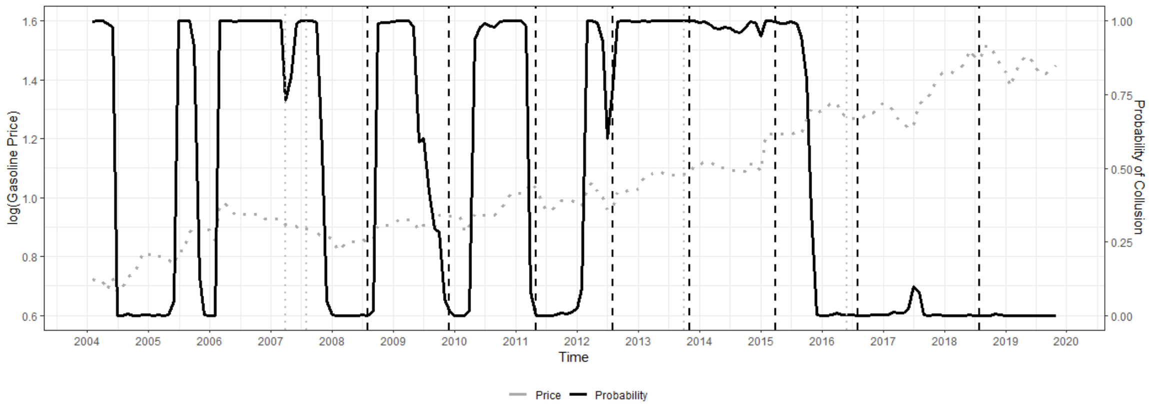

Figure 12: Londrina - collusion probabilities and breaks (2004-2019). The gray doted lines indicate the price evolution and official cartel dates, the black dashed lines are the breaks estimated in Bai Perron Test (homogeneity and $h = 10$).

Finally, to test our results reliability, we ran, once more, the conduct parameter estimation over the regime changes identified by switching regressions. Our findings showed that, between June 2005 and December 2007, λ_p was higher than in any other period. Relying on our parameter estimation, it's also possible to say that there was a competitive phase from January until July 2008. On some level, this market tendency changed to a more collusive pattern after 2008, a new regime that, with some price wars, was prevalent until the end of 2015. All parameter changes were statistically significant for Londrina's sample.

Table 12: Londrina - conduct parameter

Periods	Parameter	F	p-value
Jan-2004 to May-2005	0.072	-	-
Jun-2005 to Dec-2007	0.121	17.08	0.0000
Jan-2008 to Jul-2008	0.023	63.32	0.0000
Aug-2008 to Dec-2015	0.064	16.02	0.0000
After Jan-2016	0.027	49.15	0.0000

F-statistics are testing the significance of variation on conduct parameter between periods.

7 Policy aspects and conclusions

Concerns about analyzing antitrust policy effectiveness have been increasingly considered in the empirical literature and the government agents' practice. As Ordóñez-de Haro and Torres (2014) points out, this assessment should be made considering the ability to prevent, identify, and punish anti-competitive behavior. But punishment policies are not so valued if they fail to restore adequate competition levels in target markets, improving consumers' welfare and social distribution of wealthy, which is crucial for unequal countries like Brazil.

Usually, these policies' success has been measured through methodologies focused on estimating the impact of antitrust enforcement on prices. From this point of view, the empirical results have been relatively mixed. it's not uncommon cases where the outcome of litigation against price-fixing schemes is well below expectations. The results heterogeneity might be explained by a whole spectrum of possible post-cartel behaviors: during antitrust litigation, markets can face a hysteresis effect, changing pricing strategy to avoid high penalties; can also observe a kind of tacit collusion; or, if conditions are favorable to conspiracy, the cartel may be re-establish. That's why studying the market dynamic after the authority's raid against a specific cartel is crucial for IO and competition policy literature. For this purpose, models that try to define the evolution of the affected market endogenously are fundamental, including to attest the credibility of the results obtained with the most traditional approaches.

As shown before, when relying only on official documents to define dates and events that will impact their estimation process directly, researchers are severely exposed to the possibility of end up with misleading results, as correctly argued Boshoff and van Jaarsveld (2019) and Boswijk et al. (2019). That's why, in this paper, we left aside the concern of just measuring the effect on prices and adopted a broad overview through market evolution under antitrust litigation, using techniques such as structural breaks tests and Markov switching regressions to analyze whether there was any observable consequence of the action of the Brazilian antitrust authority in the retail gasoline market. In addition to its relevance to competition policy in general, this work also contributed to applied research on the sense that, as far as we know, it's the first to systematically compare two endogenously cartel dating approaches and, further, to propose combining them with IO model of conduct parameter to help identify collusion regimes and, somehow, check the reliability of the results from structural breaks and switching regressions approaches.

Regarding the methodological issues, our findings showed that Markov regressions were more robust to the purpose of scrutinizing the evolution of price-fixing schemes in fuel markets. This is so because its results are more sensible and more straightforward, and less likely to miss shorter regimes changes. The structural break test's significant problem is its need for a minimum size between break intervals, which strongly depends on our sample's number of observations. Since we have theoretical and empirical reasons to suspect that collusion in fuel markets is, although common, unstable, Bai and Perron's analysis end up being too sensitive to trimming parameter choice. When the minimum size between breaks is decreased, the test obtains many break dates, and it's hard to interpret without previous knowledge. With larger trimming parameters, results have better convergence properties but fail to identify some episodes. We ran a simple simulation comparing methodologies performance in a two regimes series with low and high persistence to illustrate this point. Results can be checked in the appendix C.

On the other hand, it can be argued that only two regimes (collusive or non-collusive) in the fuel market samples are artificially defined, which would be the downside of the MRS.o Unfortunately, the type of data generated in this market doesn't have enough variations to estimate three or more regimes (collusion, competition, and price war, for example). In the end, we must recognize that sometimes there is a trade-off, and maybe the better option is to combine the two techniques even if one of them is playing the role of reliability test.

On the competition policy aspects, this work presented some extremely relevant findings. If our models are reasonably accurate, the current policy's ability to restore the expected levels of competition in the cartel-hit market is seriously in doubt. In three out of four cases studied (Belo Horizonte, São Luís, and Londrina), antitrust action had, at most, restricted effects. There is evidence that dawn raids sometimes temporarily disrupt collusion agreements but do not extinguish it if market conditions remain the same. Also, the impact of fines imposed on scheme participants is mitigated when established after years of litigation (and, in Brazil, are always questioned in Court). Brasília's case, however, seems paradigmatic of how strong preventive measures combined with structural ones, aiming at market reorganization, are supposed to have lasting effects against price-fixing behavior.

This lesson goes in the same direction advanced by one of the experiments mentioned earlier in this paper (Chowdhury and Crede, 2020). A history of price coordination reduces uncertainty between agents involved in collusion and strengthens cartel's capacities, even allows it to take a tacit form. So, it's often necessary for the antitrust authority to act, breaking down entry barriers and adding new players to the market (a rematching, as happened when CADE imposes on Cascol the disinvestment in some of its fuel stations). Market forces are more effective in deterring cartel formation, and the changes in Petrobras pricing policy that took place in 2016 is another example and maybe one of the reasons for less prevalence of collusion recently. Unfortunately, our empirical design does not sufficiently control this hypothesis to make any causal relation, which should be an issue for further research.

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A Markov Switching transition matrices

Table 13: Brasília - transition matrix

	Competition	Collusion
Competition	0.932	0.068
Collusion	0.065	0.935
Expected durations	14.831	15.267

Table 14: Belo Horizonte - transition matrix

	Competition	Collusion
Competition	0.955	0.045
Collusion	0.127	0.873
Expected durations	22.374	7.857

Table 15: São Luís - transition matrix

	Competition	Collusion
Competition	0.93	0.07
Collusion	0.149	0.851
Expected durations	14.279	6.722

Table 16: Londrina - transition matrix

	Competition	Collusion
Competition	0.93	0.07
Collusion	0.071	0.929
Expected durations	14.378	14.051

B Structural model (conduct parameter) outputs

Table 17: Brasília - Structural model (conduct parameter)

Demand Eq.		Pricing Eq.	
Constant	0.9708	Constant	1.529656***
	(2.097)		(0.378)
Gasoline Retail Price	-3.281***	Gasoline Wholesale Price	0.9002863***
	(0.1494)		(0.051)
Etanol Price	2.248***	Labor Costs	-0.0003763***
	(0.273)		(0.0001)
Cars	0.000036***	λ_p: Jan-2012/Feb-2016	0.089*
	(0.000003)		(0.052)
Economic Activity Index	0.068***	λ_p: After Mar-2016	0.018
	(0.0090)		(0.048)
R^2	0.881	R^2	0.898
Observations	78	Observations	78
Period	2012M01 2019M07	Period	2012M01 2019M07

Dependent variables: sales and gasoline retail prices, respectively (source: ANP). Instruments: excluded cost and demand factors and lagged gasoline and ethanol prices Coefficients with ***, **, and * are significant at level 1, 5, and 10%.

Table 18: Belo Horizonte - Structural model (conduct parameter)

Demand Eq.		Pricing Eq.	
Constant	7.548***	Constant	0.297***
	(0.969)		(0.088)
Gasoline Retail Price	-2.83***	Gasoline Wholesale Price	1.001***
	(0.176)		(0.020)
Etanol Price	1.95***	Labor Costs	0.0001
	(0.205)		(0.00008)
Cars	0.00000046***	λ_p: Jan-2004/Feb-2007	0.052**
	(0.00000012)		(0.021)
Economic Activity Index	0.032***	λ_p: Mar-2007/Mar-2008	0.088***
	(0.005)		(0.021)
		λ_p: Apr-2008/Jan-2011	0.033**
			(0.016)
		λ_p: Feb-2011/May-2013	0.067***
			(0.013)
		λ_p: After Jun-2013	0.017
			(0.013)
R^2	0.875	R^2	0.968
Observations	179	Observations	180
Period	2004M01 2018M12	Period	2004M01 2018M12

Dependent variables: sales and gasoline retail prices, respectively (source: ANP). Instruments: excluded cost and demand factors and lagged gasoline and ethanol prices Coefficients with ***, **, and * are significant at level 1, 5, and 10%.

Table 19: São Luís - Structural model (conduct parameter)

Demand Eq.		Pricing Eq.	
Constant	-0.612***	Constant	-1.061 ***
	(0.158)		(0.033)
Gasoline Retail Price	-0.415***	Gasoline Wholesale Price	1.419***
	(0.021)		(0.039)
Etanol Price	0.542***	Labor Costs	0.001
	(0.022)		(0.0007)
Cars	0.000003***	λ_p: Jan-2004/Oct-2006	-0.032
	(0.0000001)		(0.033)
Economic Activity Index	0.011***	λ_p: Nov-2006/Dec-2009	0.059*
	(0.0008)		(0.033)
		λ_p: After Jan-2010	-0.002
			(0.015)
R^2	0.980	R^2	0.951
Observations	180	Observations	191
Period	2004M01 2018M12	Period	2004M01 2018M12

Dependent variables: sales and gasoline retail prices, respectively (source: ANP). Instruments: excluded cost and demand factors and lagged gasoline and ethanol prices Coefficients with ***, **, and * are significant at level 1, 5, and 10%.

Table 20: Londrina - Structural model (conduct parameter)

Demand Eq.		Pricing Eq.	
Constant	2.34***	Constant	0.217
	(0.240)		(0.210)
Gasoline Retail Price	-0.362***	Gasoline Wholesale Price	1.030***
	(0.043)		(0.035)
Etanol Price	0.221***	Labor Costs	0.0006
	(0.032)		(0.0004)
Cars	0.0000008***	λ_p: Jan-2004/May-2005	0.072**
	(0.0000001)		(0.036)
Economic Activity Index	-0.004***	λ_p: Jun-2005/Dec-2007	0.121***
	(0.001)		(0.035)
		λ_p: Jan-2008/Jul-2008	0.023
			(0.040)
		λ_p: Aug-2008/Dec-2015	0.064*
			(0.033)
		λ_p: After Jan-2016	0.027
			(0.030)
R^2	0.692	R^2	0.941
Observations	170	Observations	180
Period	2004M01 2018M12	Period	2004M01 2018M12

Dependent variables: sales and gasoline retail prices, respectively (source: ANP). Instruments: excluded cost and demand factors and lagged gasoline and ethanol prices Coefficients with ***, **, and * are significant at level 1, 5, and 10%.

C Simple simulation: MRS and structural changes

Aiming to demonstrate the relationship between Markov Switching Regressions technique and structural break tests, we performed a simple simulation exercise. Suppose that, in some market, retail prices follows a Markovian DGP, with two regimes, and the following deterministic formulations:

$$p_t = \begin{cases} 0.2 + 1.1c_t - 0.05d_t, & s_t = 1(collusion) \\ 0.0 + 1.1c_t + 0.05d_t, & s_t = 2(non - collusion) \end{cases} \tag{11}$$

Where c_t represents the costs and d_t the demand shifters and S_t is the discrete state variable that defines the regime. The first equation represents a collusive regime ($s_t = 1$), in which there is an increase in the price level (intercept) and, as in Rotemberg and Saloner model, there is an anti-cyclical response to demand. The second is defined as a kind of oligopolistic market regime ($s_t = 2$) where agents establish a small markup on costs. In our simulation study, Markov transition matrices have two possible profiles, with high or low persistence regimes, as shown in table 21.

Table 21: Simulation - transition matrices

High Persistence

	Competition	Collusion
Competition	0.99	0.01
Collusion	0.05	0.95

Low Persistence

	Competition	Collusion
Competition	0.95	0.05
Collusion	0.15	0.85

To simulate our market, also consider that the cost and demand vectors have their own DGPs, characterized by an AR (1) process, with *idd* shocks (ϵ_t and v_t), and a specific intercept:

$$\begin{cases} c_t = 1.0 + 0.8c_{t-1} + \epsilon_t, \\ d_t = 0.2 + 0.9d_{t-1} + v_t \end{cases} \tag{12}$$

This basic model generated two price series with 300 observations each, as can be seen in figures 13 and 14. Estimating a model of Markovian Regressions, we may obtain the filtered and smoothed probabilities observed in figures 15 and 16.

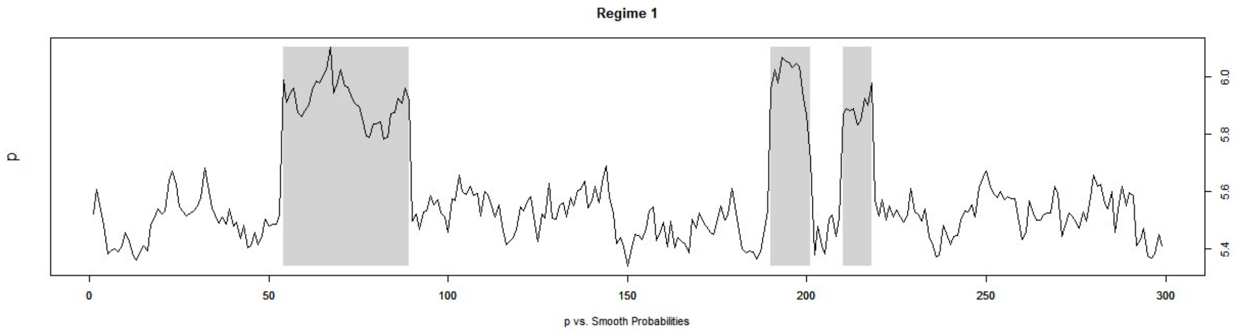

Figure 13: Simulation - simulated price series with two high persistence regimes. The gray shaded area indicates the collusion regime.

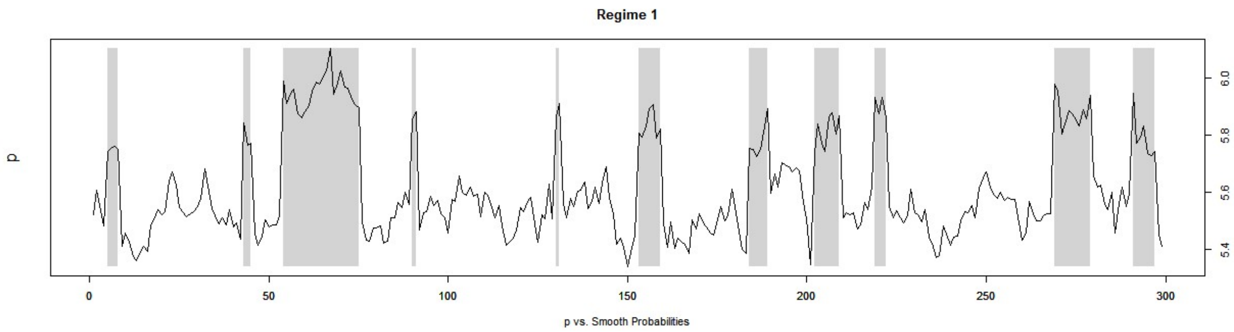

Figure 14: Simulation - simulated price series with two low persistence regimes. The gray shaded area indicates the collusion regime.

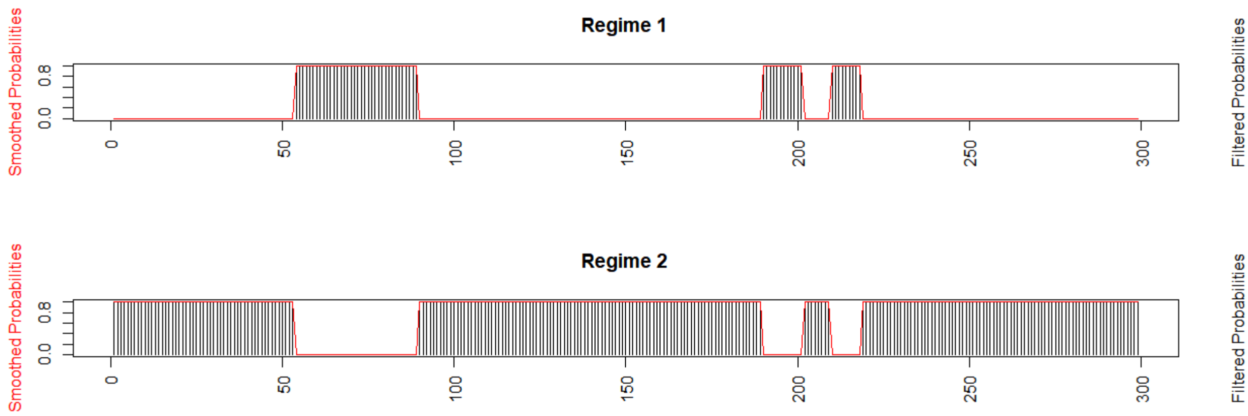

Figure 15: Simulation - smoothed and filtered probabilities for high persistence regimes. Regime 1 is the collusive one.

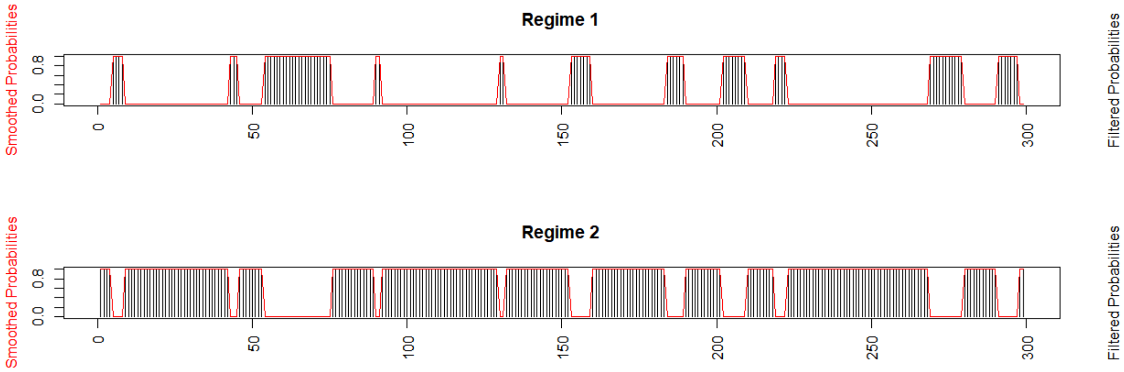

Figure 16: Simulation - smoothed and filtered probabilities for low persistence regimes. Regime 1 is the collusive one.

It's worth noting that the series with low persistence (a DGP more like our set of cartel cases in the fuel market) presents several short periods of collusion (11 episodes of a cartel, with 22 structural breaks), followed by others of competition. On the other hand, in series with high persistence, there are fewer regime changes (only three periods of a cartel and six breaks) and more observations between them. So, let's check how Bai and Perron's test performed when estimating structural breaks for these two series, allowing for changes in the crucial trimming parameter (h). Our estimation's primary results, the observations where Bai and Perron's test signaled a structural break, can be seen in table 22.

Table 22: Simulation - Breaks identified by Bai and Perron's test (observations)

h	High Persistence	Low Persistence
0.15	45, 89, 174, 218	53, 100, 183
0.10	53, 89, 189, 218	42, 75, 152, 183, 222, 268
0.05	53, 89, 187, 201, 218	53, 75, 152, 166, 183, 209, 223, 268, 282
0.02	6, 53, 65, 89, 99, 144, 189, 201, 209, 218, 227, 237	8, 42, 47, 53, 75, 89, 94, 129, 134, 152, 159, 183, 189, 201, 209, 217, 222, 268, 279, 286, 291

We did not perform a Monte Carlo simulation with hundreds of simulated samples because our goal was only to illustrate conclusions about the downsides of structural breaks tests. However, just with this simple exercise, we could show that structural break test performance is not satisfactory when there are recurrent regime changes in the market. In our series of low persistence regimes, with a trimming parameter of 0.15, the estimation found only 3 out of 22 breaks. When the minimum number of observations between sample partitions are reduced, the test showed better results, signaling more correct breaks. But this gain in reducing the type II errors came with losses in robustness for the type I. It's worth noting that with $h = 0.02$, the test returns a significant number of false breaks (a phenomenon explained by the terrible convergence proprieties when there are only six observations between intervals).